

INTRODUCTION

Photogrammetry is a process that takes two-dimensional images of an object or environment and creates a three-dimensional digital model from them using specialized processing software. By creating 3D models, researchers can explore new possibilities for digital documentation of artifacts while also conducting analytical applications in various disciplines. Current off-the-shelf photogrammetry software is not as geometrically accurate as LIDAR or structured light capture, but researchers have investigated various factors when taking images in order to produce the best model with existing software. For example, Dai et al. discovered that possible deviations in the resulting model can stem from factors such as camera lens distortion, capture settings, and processing software programs.^[1]

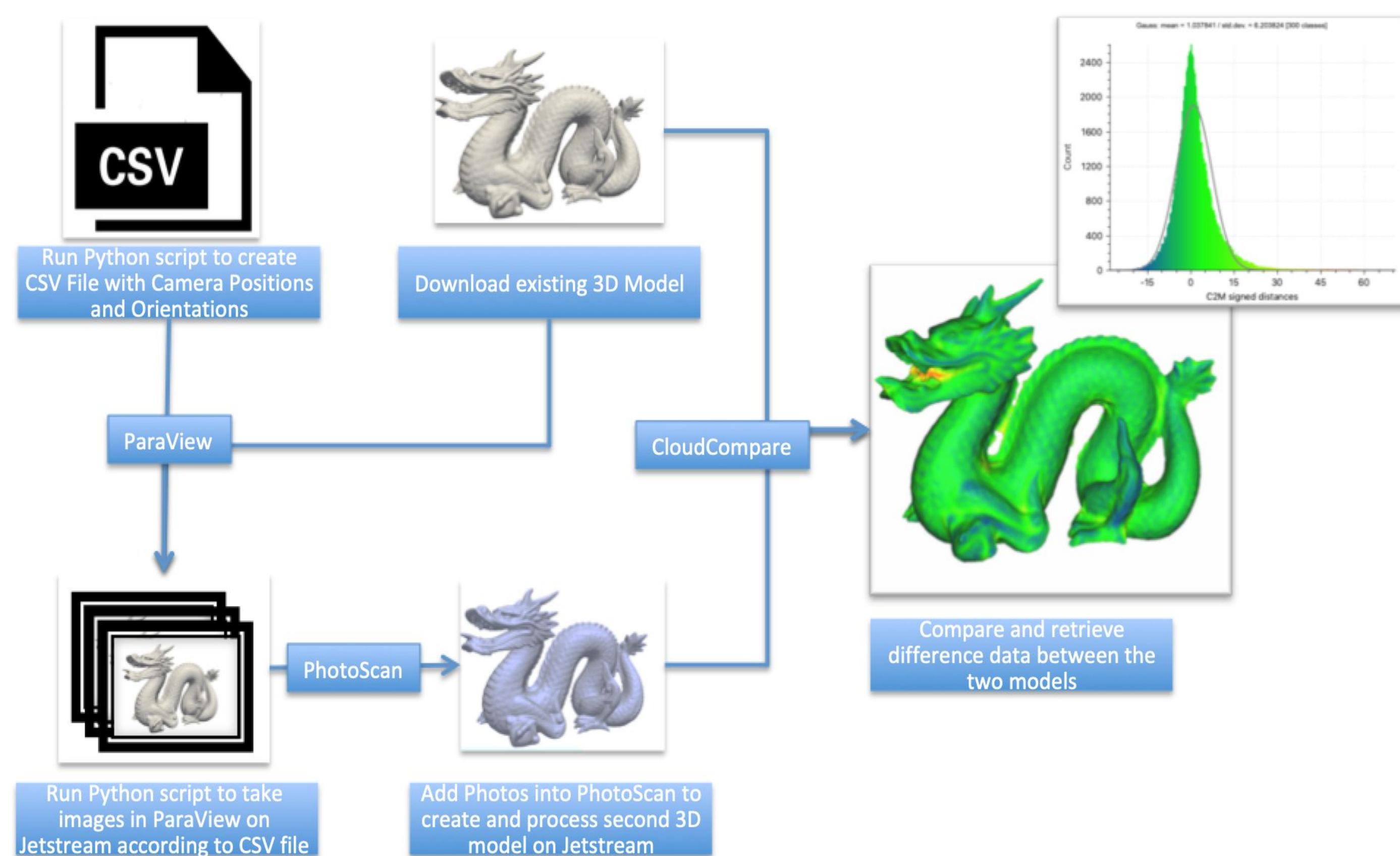


Figure 1: Synthetic Photogrammetry Workflow

METHODS

Synthetic Photogrammetry

Given the numerous potential sources of error in photogrammetry, our aim is to develop a technique that quantifies the relative impacts of these error sources so that we can offer recommendations for taking an optimal set of photographs of a given object or environment. This technique is called “synthetic photogrammetry” and is used to generate images in precise positions and orientations while also controlling causal factors such as background, lighting, and surface properties. This technique also allows the original digital model to serve as the ground truth for objective comparison with the photogrammetrically generated models. The synthetic photogrammetry workflow we used is shown in Figure 1. We iterated the process over the four variables shown in Table 1 for the three models shown in Table 2.

Number of Images	Resolution	Camera Distance	Orbital Pattern
144 images	1600 x 900	Closer (2500 units)	Spherical
288 images	4160 x 2690	Further (3500 units)	Cylindrical
576 images	6720 x 4480		

Table 1: Table of parameters evaluated through synthetic photogrammetry

Jetstream

To streamline the process of synthetic photogrammetry, we employed Python script automation and cloud computing. Python scripts were used to generate image positions and orientations in a CSV file, which were then used to render images in ParaView (v.4.4.0); the resulting ParaView images were used to build models in Agisoft PhotoScan (v.1.4.4). All processes were executed and sped up on a virtual machine via the XSEDE cloud computing resource Jetstream, which provides easy access to cloud computing for researchers in the “long tail of science.”^[2,3]

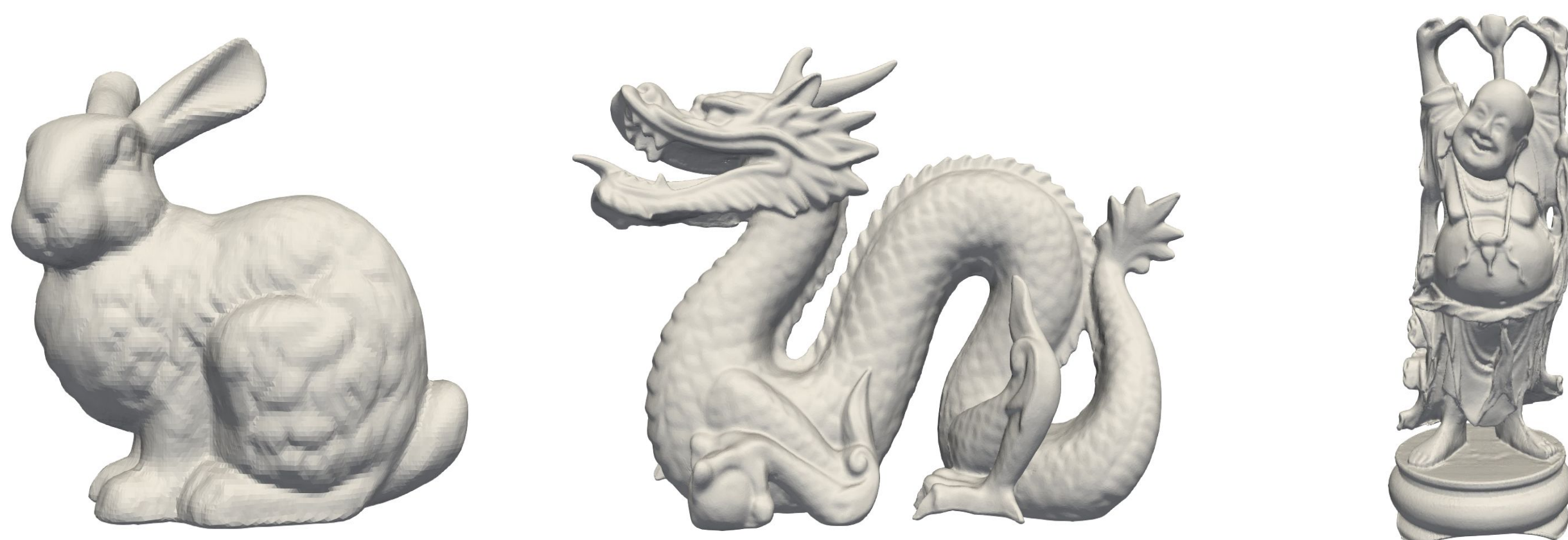


Figure 2: Models of Stanford Bunny (69K polygons), Dragon (1.13M polys), and Happy Buddha (1.09M polys) representing simple, complex, and human-like shapes to be photogrammetized

Models

We used the Dragon, Bunny, and Happy Buddha models digitized by the Stanford University Computer Graphics Laboratory using the Cyberware 3030 MS Scanner uploaded onto Stanford’s 3D Scanning Repository.^[4]

RESULTS

We used CloudCompare (v.2.10.2) to examine the Gaussian distribution of the signed distances between the original and photogrammetized models. The Gaussian distribution yielded a standard deviation, which represents the overall accuracy of the synthetic models compared to the original. Figure 3 shows 3D representations of the dragon generated with a spherical image pattern and different image counts and resolutions; the colors represent the error in the generated model. Figure 4 graphs the impact of changing image resolution, camera distance, and number of pictures on the overall accuracy of the resulting model, again using the dragon with a spherical pattern. To give the standard deviations a relative scale, the unit dimensions of the dragon are 2048w x 1444h x 916d.

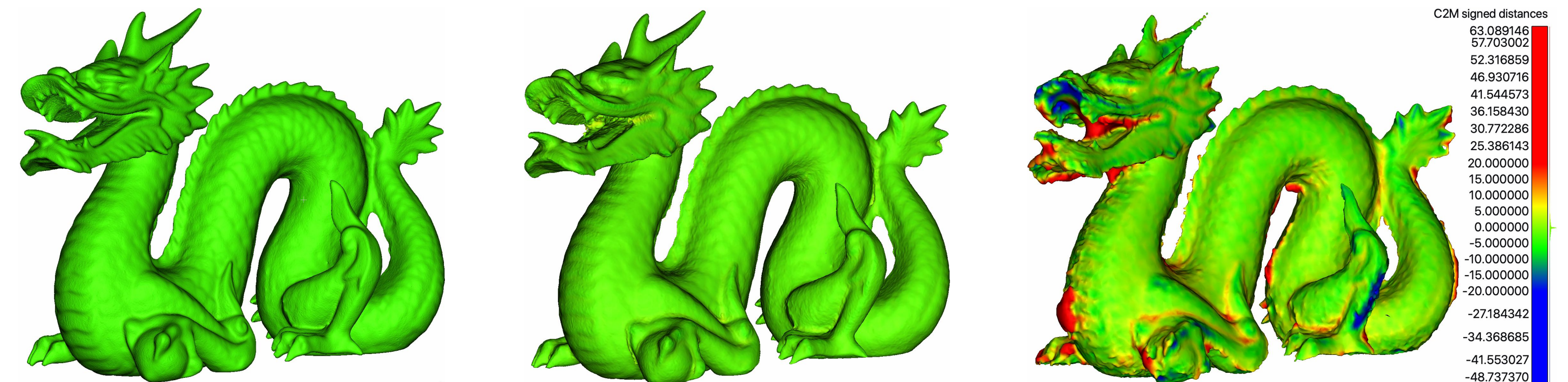


Figure 3: Dragon Synthetic Models

Left: 576 images, 6720x4480 resolution, 2500 distance → 0.377219 standard deviation
Middle: 288 images, 4160x2690 resolution, 3500 distance → 1.71638 standard deviation
Right: 144 images, 1600x900 resolution, 2500 distance → 7.04424 standard deviation

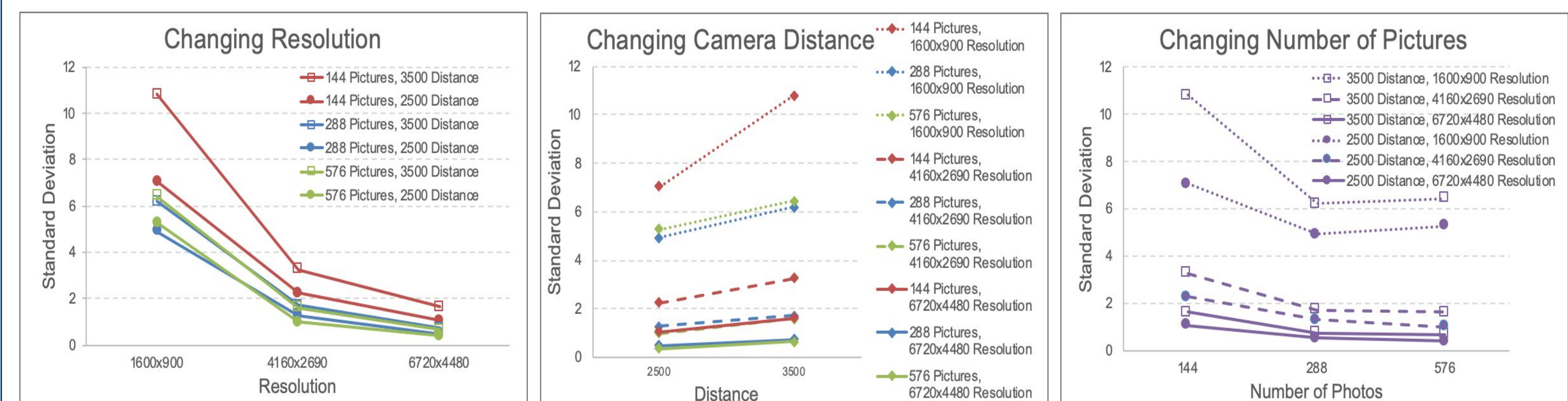


Figure 4: Standard Deviation of Mesh Error across changing parameters

In Figure 4, it is clear that increasing resolution yields lower standard deviations, and decreasing the distance from the object lowers the standard deviation. As for the number of pictures, increasing the number does decrease the standard deviation to an extent, but any further increase in the number of pictures does not decrease the standard deviation as much. The best model with the lowest standard deviation occurs when the resolution is highest, number of photos is highest, and the distance is closest. Moreover, the visualizations in Figure 3 help indicate the geometric accuracy in specific areas of the models.

Not surprisingly, our work confirms that increasing the number, resolution, and detail (closer distance) of images will increase the accuracy of the resulting model; however, higher resolutions and image counts also increase the runtime of the photogrammetry processing. So when planning image acquisitions, users must balance the increase in accuracy with the increase in processing time. Table 2 lists the runtimes and accuracies (error standard deviations) for different image counts and resolutions for the dragon model at closer camera distance.

	Runtimes			Mesh Accuracy (StdDev of Error)		
	in minutes (normalized to fastest)			in model units (normalized to smallest)		
	Number of Images			Number of Images		
Resolution	144	288	576	144	288	576
1600 x 900	6 (1.0)	31 (5.2)	222 (37.0)	7.04 (18.7)	4.92 (13.0)	5.28 (14.0)
4160 x 2690	54 (9.0)	230 (38.3)	1,276 (212.7)	2.25 (6.0)	1.28 (3.4)	1.00 (2.6)
6720 x 4480	156 (26.0)	570 (95.0)	3,320 (553.3)	1.05 (2.8)	0.50 (1.3)	0.38 (1.0)

Table 2: Runtimes and Mesh Accuracy for Dragon synthetic model

CONCLUSION

Photogrammetry has a myriad of applications and great potential to expand. As software and capture methods continue to improve, objective testing and analysis of photogrammetry techniques becomes essential. We have shown that our synthetic photogrammetry workflow is a successful and efficient method for testing and experimentation that can precisely control causal factors. We used our workflow to confirm that the following four factors have a positive effect on the accuracy of the resulting model: increasing image count (to an extent), increasing image resolution, decreasing camera distance, and using an orbital pattern that fits the shape of the model. With numerous other variables to be considered, synthetic photogrammetry will be a flexible and repeatable method for additional testing and experimentation.

References

- [1] F. Dai, et al. Photogrammetry error sources and impacts on modeling and surveying in construction engineering applications. Visualization in Engineering. 2014.
- [2] C. A. Stewart, et al. Jetstream: a self-provisioned, scalable science and engineering cloud environment. In Proceedings of the 2015 XSEDE Conference: Scientific Advancements Enabled by Enhanced Cyberinfrastructure. 2015.
- [3] C.A. Stewart, et al., Jetstream: performance, early experiences, and early results. In Proceedings of the XSEDE16 Conference on Diversity, Big Data, and Science at Scale. 2016.
- [4] All models are sourced by Stanford University Computer Graphics Laboratory. The Stanford 3D Scanning Repository. 2014. Retrieved from <http://graphics.stanford.edu/data/3Dscanrep/>

Acknowledgements

This material is based upon work supported by the National Science Foundation under Grant No. 1445604. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. Special thanks to Winona Snapp-Childs and Harmony Jankowski for revising and editing our poster and to Katie Chapman for helping us through the photogrammetry process. Thank you also to Steve Bird for guiding us through the Jetstream configuration.